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Grading of Iranian's Export Pistachio Nuts Based on Artificial Neural Networks

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ABSTRACT

In this paper an intelligent separation system, based on artificial neural networks (ANNs), for classifying four different varieties of Iranian *pistachio* nuts, namely, Kaleghouchi (Ka), Akbari (Ak), Badami (Ba) and Ahmadagaee (Ah) is presented. To develop the ANN models a total of 3200 pistachio sound signals, 800 samples for each variety, were recorded. Features of pistachio nut varieties were extracted from analysis of sound signal in both time and frequency domains by means of Fast Fourier Transform, power spectral density and principal component analysis methods. Altogether forty features were selected as input vector to ANN models. Network output vector consisted of four neurons for classification of varieties. Collected data for 3200 pistachio nuts were divided into three sets: 70% (2240 data points in total) for training, 15% for testing, and the remaining 15% were used for cross validation of ANN models. In developing the ANN models, twelve ANN architectures, each having different numbers of neurons in hidden layer, were evaluated. The optimal model was selected after several evaluations based on minimizing of mean square error (MSE), correct separation rate (CSR) and coefficient of correlation. Selected optimal ANN for classification was of 40 – 12 - 4 configuration. CSR of proposed optimal ANN model for four pistachio varieties, Ka, Ak, Ba and Ah, were 96.97%, 97.64%, 96.36% and 99.10%, respectively. Net weight average of system accuracy was found to be 97.51%.

Key Words: Artificial neural networks; Pistachio nuts; Classification; Acoustic; Principle component analysis

INTRODUCTION

Pistachio (*Pistacia vera* L.) is a dry-climate deciduous tree producing nuts in clusters. Pistachio nuts differ in appearance and quality. From botany point of view, more than 60 varieties of pistachio nuts have been identified in Iran. By producing approximately 300 million kg per year, Iran is the world's leading pistachio nut producer (Alikhani, 2002). About 80% of Iranian pistachio is supplied to the world markets on whole-sale value of nearly US$ 3 - 3.5 kg^{-1} (Ministry of Agricultural Jahad-Iran, 2002). Nuts are harvested by hand picking, by knocking them off the tree with poles or shaking trees using mechanical shakers. Harvested nuts must be dehulled, dried and sorted. Preliminary separation of lower quality nuts is usually done by floatation or with mechanical separators. Final separation and inspections, prior to packaging, are done manually or by electromechanical devices. Mixing of pistachio nuts of different varieties may occur as a result of mixed plantation, during harvesting, transportation, handling and storage. Separation of the mixed nuts is important for both economical as well as aesthetical reasons, and to offer consumer a uniform product. Due to closeness of physical sizes, morphological and optical properties of the nuts, a fully efficient separation could not be accomplished through mechanical or electro-optical devices. Inspection and separation by hand is tedious and often does not bring the desired results. The task of classification could most efficiently be performed by a machine vision system with multiple features of processing capabilities. This method has been successfully used previously in separation of different agricultural products such as apples, oranges, tomato and raisins. Ghazanfari and Irudayaraj (1996a) used string matching technique for classification of four varieties of Iranian pistachio nuts, based on their two dimensional shapes. The classification accuracy for Kalegouchi, Akbari, Ohadi and closed shell Ohadi were 90%, 94%, 88% and 90%, respectively. Ghazanfari *et al*. (1996b) used a combination of machine vision as well as Artificial Neural Network (ANN) techniques for classification of these four varieties. Using this technique, it is possible to achieve separation accuracy of 96%, 97.3%, 93.3% and 97.3%, for Kalegouchi, Akbari, Ohadi and closed shell Ohadi, respectively.

Sorting systems have to be flexible in use, due to the wide variety of products available in the market. On the other hand, the need to be able to test new products requires a high degree of processing adaptability. The test system should not require lengthy resetting times or complex (software) engineering. It is for this reason that one has to rely upon intelligence trainable systems. Training means that the test system picks up randomized selected specimens. The robustness, capability of approximating a posterior distribution and high potential for parallel processing makes ANN a suitable choice for classification of agricultural products. Kavdir and Guyer (2002) sorted Empire and Golden delicious apples based on their surface quality conditions, using backpropagation neural networks and spectral imaging. To separate Empire and Golden delicious apples into two classes of defective and non-defective, success in classification ranged from 89.2% to 100%. In separating apples of Empire and Golden delicious into five classes (four for defective ones & one as wholesome) classification success for Empire apples was between 93.8% and 100%, while success in classification for Golden delicious apples was between 89.7% and 94.9% based on the features employed.

Recently, acoustical experiments (non-destructive tests) have been increasingly employed in agriculture. Garsia *et al*. (2003) applied this technique for classification of fruits by determining the ripeness or stiffness. Pearson (2001) used discriminant analysis on data obtained from sound signal sampling, in time domain, for separation of open and closed shell Kerman variety of pistachio nuts. The classification accuracy of this method was approximately 97%. Quit recently, Cetin *et al*. (2004) used voice recognition technique for separation of open and closed shell pistachios nuts based on their impact acoustics. Features extracted from sound signals consisted of Mel–Cepstrum coefficients and eigenvalues obtained from principal component analysis (PCA) of autocorrelation matrix of the sound signals. The classification accuracy for closed shell nuts exceeded 99%.

So far there have not been any reports on combining ANN and acoustical technique for classification of pistachio nut varieties. Development of open and closed shell pistachio automatic sorting system based on a combination of ANN and acoustical technique is currently underway by us. The initial results and findings were presented by Mahmoudi *et al*. (2005) at ISHS. Due to importance of separating different pistachio nut varieties, from viewpoint of economy, quality, export, marketing, tediousness of manual separation along with low accuracy, this study was performed as an approach to tackle the problem. In the ongoing study the results of application of non-destructive acoustic technique incorporated with ANN for classification of four different varieties of Iranian pistachio nuts, namely, Kalehghouchi (Ka), Akbari (Ak), Badami (Ba) and Ahmadagaee (Ah) shown in Fig. 1, are presented. The aim of this study was to design and present a suitable algorithm for identification and separation of these pistachio nuts varieties.

MATERIALS AND METHODS

In order to devise a separation system for the four different pistachio nut varieties shown in Fig. 1, 800 nuts of each variety are selected. To train the system on how to differentiate between these varieties, traditional procedures for system modeling become un-manageable or virtually insoluble if either the basic system can no longer be adequately linearly approximated or if a large number of measured variables (features) have to be considered simultaneously. One approach to avoid these drawbacks is using automatic trainable classifier, such as artificial neural networks (ANNs). Scheme of such a proposed system is illustrated in Fig. 2 (detailed explanations are subsequently presented).

A Panasonic Electret capsule microphone (VM-034CY) was employed for detecting sound signals in nuts. The microphone was installed inside an isolated acoustic chamber to eliminate environmental noise effects. The sensor picks up the impact of sound and sends the data, in real-time, to a PC based data acquisition system via a sound card. Feature extraction is performed on the collected data. The objective of feature extraction block is to select the significant features in the signal with reference to the subsequent differentiation of the various system states to be performed in the classifier. The input signal for the block "feature extraction" represents the digital sound signal in time domain with the output from this stage being the feature vector (see Fig. 2). Signal analysis procedures from the time domain (e.g. peak values), the frequency domain (e.g. FFT, PSD & Phase) and statistical methods (e.g. PCA) are then used for feature extraction. These features are fed to classification system. The classification was performed with ANNs. There are several types of ANNs, each with its own advantages and drawbacks. Neural networks are procedures for statistical specimen recognition. In a training process, the classifier is given specimen signals, then sets its weight coefficients in the training phase so that it is able to reproduce the classification results as adequately as possible. The individual system states are represented at the input of the stage for knowledge based interpretation by a class statement based on available expert knowledge. This expert knowledge was then fed to the system in the training phase.

The system was designed to feed pistachio nuts to an impact surface, catch the sound signal upon impact, process the data and divert the product into four streams (Fig. 3). Electret capsule microphone sensor as sound signal detector, was located under the steel plate, inside a noise isolated acoustic chamber. Impact sound signals, which were caught by the sensor are sent to the PC based data acquisition system via an onboard sound card (Intel® 82801 BA/BAM AC`97Audio controller). Data acquisition system acquired, saved and processed data at a sampling rate of 0.023 ms. Finally a classification algorithm separates pistachio nut varieties based on ANN. The impact plate was made up of 140×140 mm polished steel bar. A high thickness (10 mm) was required to minimize vibration of bar when impacted by a pistachio nut. It was found that 60° was the optimal angle of inclination. If the slide is inclined more steeply, the nuts are more likely to tumble (Mahmoudi *et al*., 2005).

Preliminarily experimental results indicated that steel

Fig. 1. The typical images of four varieties of pistachio nuts

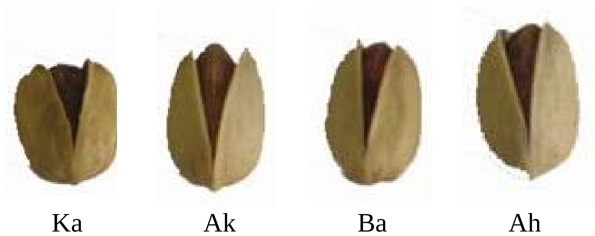


Fig. 2. An ANN based separation system for classification of pistachio nuts varieties

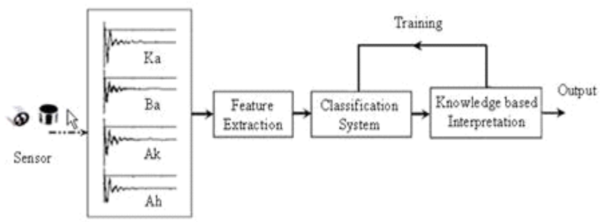
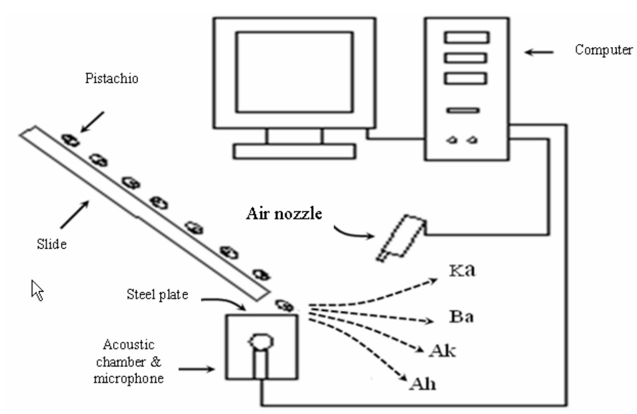


Fig. 3. Schematic of recognition and separation system



plates proved better than glass or wooden for separating different pistachio nut sounds (Mahmoudi *et al*., 2005). The Microphone was housed inside an acoustic chamber. The acoustic chamber was made up of wood and filled with glass wool, rubber and wood. The selected materials for chamber structure were good absorbers preventing the chamber from acoustic reflection. Therefore, environmental sounds could not reach the microphone. Microphone output was connected to the sound card in a Pentium IV personal computer (PC). PC was used for acquiring, saving and processing of data.

The pistachio nuts, collected from 2004 harvest season, were manually sorted into four classes in accordance with their commercial varieties. The respective varieties are shown in Fig. 1. Each class consisted of 800 nuts, which were randomly selected and fed to the sorting system one at a time. Sound signal data in time domain were saved for subsequent analysis (Fig. 2). Data acquisition Toolbox from Matlab software (www.mathwork.com) was used for data collection. Since the maximum frequency (sampling rate) of used sound card was equal to 44/1 kHz, data acquisition continued for 5.67 ms after triggering. This produced 250 data points for each nut.

The Fast Fourier Transform (FFT) is an algorithm for calculating the Discrete Fourier Transform (DFT). FFT utilizes sharp algorithms does as DFT, but in much less time. DFT is extremely important in the area of spectral analysis because it takes a discrete signal within the time domain and transforms that signal into its discrete frequency domain representation. Without a discrete-time to discrete-frequency transform one would not be able to compute the Fourier transform with a microprocessor or DSP based system. Feature extraction from impact sound is the first step for designing a successful pistachio nut classification system (Fig. 2). Useful features can be extracted, for input vector to ANN model, by considering signal amplitude in time domain and calculation of magnitude, phase and power spectral density (PSD) of FFT components in frequency domain (Fig. 4, 5 & 6).

Data acquisition continued for 5.67 ms after triggering, producing 250 data points in time domain per nut (Fig. 2). For calculating amplitude, phase ($|Y(\omega)|$, $\angle Y(\omega)$) and PSD in frequency domain. A 1024-point FFT was performed (Fig. 4, 5 & 6). According to symmetry of sound signal in Frequency domain, only 512 data from 1024 data point were used for calculating PSD and phase (Fig. 5 & 6). A total of 1274 features were obtained for each pistachio nut.

For real time systems, the dimension of the input vector is large, but the components of the vectors are highly correlated (redundant). It is useful in this situation to reduce the dimension of the input vectors. An effective procedure for performing this operation is using principal component analysis (PCA). This technique is effective in three ways: (i) it orthogonalizes the components of the input vectors (so that they are un-correlated with each other) (ii) it sorts/orders the resulting orthogonal components (principal components) so that those with the largest variation come first; and (iii) it eliminates components that contribute the least to the variation in the data set. Note that input vectors must be normalized first, so that they are of zero mean and unity variance. PCA analysis was performed with Matlab software. PCA results as well as eliminated percentage of the total variation in the data set, in relation to selected principle components, are shown in Fig. 7. According to time and frequency domains analyses of sound signals three sets of features were utilized for PCA purposes. These features were; (1) Principal components obtained from PCA of signal amplitudes in the time-domain, (2) Principal components obtained from PCA of power spectral density (PSD) in the frequency- domain. For this, first the DFT of the sound signal y is obtained by taking 1024-point FFT, i.e. $Y(\omega)$ = fft (y, 1024). The PSD, a measure of the power at

Fig. 4. Average FFT magnitude of sound signals in figure 2

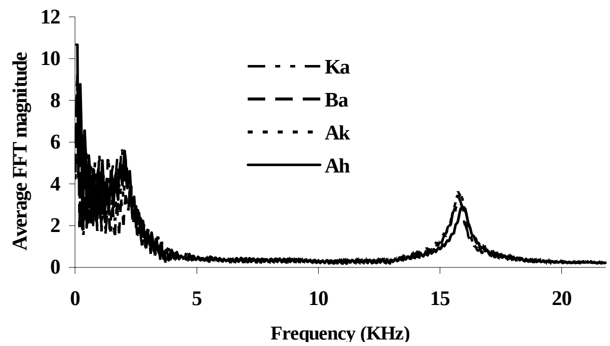


Fig. 5. Average FFT phase of sound signals in figure 2

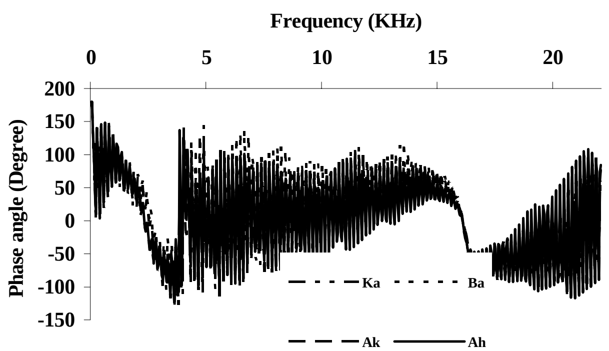
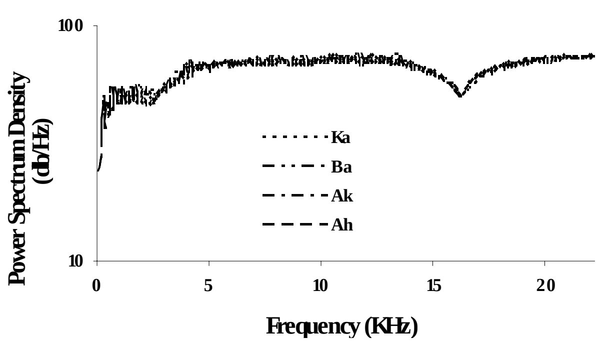


Fig. 6. Power spectral density for frequency domain signal



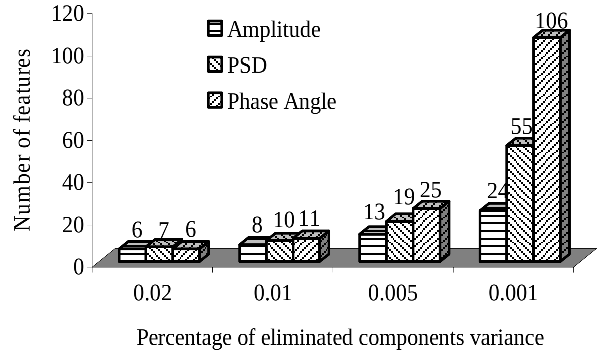
various frequencies, is then calculated from:

$$PSD = Y(\omega) \times (Y^*(\omega)/1024,$$

and (3) Principal components obtained from PCA of signal phase in frequency-domain. Phase ($\angle Y(\omega)$ of signal spectrum are calculated from FFT components of sound signal.

After normalization of data, PCA analysis was performed on data. From Fig. 7 it is clear that one can express 98% of total variations in the input data set with only six amplitude components. Therefore, features can be reduced from 250 to 6. Similarly we can express 98% of total variations in the input data set by taking only seven

Fig. 7. Relation among eliminated components variance and number of selected principle components



PSD components, i.e., in this case features can be reduced from 1024 to 7 components of PSD. Finally, by using PCA the number of phase angle features can be reduced from 1024 to 6 components. To achieve principle components variances of 99/9%, components of input vector are seriously increased (Fig. 7). This is not desired from modeling point of view. To find the best combinations and minimum number of principle components with highest accuracy, 37 different combinations of mentioned components are needed to be considered. By using PCA, a 98.26% reduction in features is achieved. These features are then fed to ANN models as input vector. In summary, the best combinations are: 24 FFT amplitude features, 10 PSD features and 6 phase features.

Artificial neural networks classifier. The multilayer perceptron (MLP) is one of the most widely implemented neural network topologies (Haykin, 1999). MLPs are normally trained with the back propagation algorithm (Rumelhart *et al*., 1986). In fact the renewed interest in ANNs was in part triggered by the emergence of back propagation learning rule. The back propagation rule propagates the errors through the network and allows adaptation of the hidden processing elements (PEs). Two important characteristics of MLP are (i) use of nonlinear PEs such as logistic or hyperbolic tangent and (ii) their massive interconnectivity, i.e. any element of a given layer feeds all the elements of the next layer. The MLP is trained with error correction learning, which means that the desired response for the system must be known a priori. After adequate training, the network weights are adapted and employed for cross validation in order to determine the ANN model overall performance. Gradient descent with momentum (GDM) learning rule is an improvement to the straight GD rule in the sense that a momentum term is used to speed up learning and stabilizing convergence (Rumelhart *et al*., 1986). Therefore, the GDM method of learning is used throughout this study. Further details about MLP and GDM can be found in any standard neural network books such as the one is written by (Haykin, 1999).

Neurosolution software was used for design and testing of ANN models (http://www.nd.com). About 15% of data were selected for cross validation and entered into model until network was prevented from overtraining (over fitting). The topology of final MLP neural network is given in Fig. 8. This figure shows a three layer network incorporating a single hidden layer of processing elements. Each PE has a weighted connection to every PE in the next layer and each performs a summation of its inputs passing the results through a transfer function - this is a linear function at the input layer and a non-linear hyperbolic tangent function at every other layer. Based on already discussed reasons 40 features selected as input of network. Therefore, input layer had 40 PE's. Each of PE's is related to an input feature. The number of nodes in the hidden layer was varied according to the number of inputs and network performance.

A learning rate of 0.7 was used throughout the momentum learning rule. Considering pistachio nut varieties, output layer had four PE's. Numbers of PE's for hidden layer were selected based on trial and error. The 3200 nut data were divided to three sets: 70% of data (2240 data points) were used for training, 15% (480 data points) for testing and the remaining 15% were used for cross validation.

In order to minimize ANN training time, only one hidden layer was considered. If the number of hidden neurons is too small, the model will not be flexible enough to model the data well. On the other hand, if there are too many layers, the model will over fit the data. By using information about mean square error (MSE) of cross validation (CV) for different ANN models, the number of PEs in hidden layer was selected to be 12 (Fig. 8). For this purpose MSE cross validation for different numbers of hidden PE's at various epochs were investigated (Fig. 9). Based on data obtained network with 12 PE's in hidden layer was observed to have the least standard deviation error as well as high stability. Therefore optimal selected model had 40 – 12 - 4 structure for classification (Fig. 9).

RESULTS AND DISCUSSION

Performance evaluations of different designed models were compared based on mean square error (MSE) and correlation coefficient (r). The formula used for determining MSE is:

$$\mathrm{MSE} = \frac{1}{NP}\sum_{j=0}^{P}\sum_{i=0}^{N}(D_{ij} - Y_{ij})^2 \qquad (1)$$

Where P is the number of output PEs, N is the number of exemplars in the data set, Y_{ij} is network output for exemplar i at processing element j and D_{ij} is desired output for exemplar i at processing element j.

Simulation results are presented in Fig. 10 and Tables I and II. In Table I, we show the number of correctly classified nuts using proposed method. After network training and validation using optimized ANN model, i.e. 40 – 12 - 4 structure, correct separation rate of four pistachio nut varieties, Ka, Ak, Ba and Ah, were found to be 96.97%, 97.64%, 96.36% and 99.10%, respectively. Their estimated MSE were 0.0141, 0.0270, 0.0193 and 0.0123 (Fig. 10), whereas the corresponding correlation coefficients were 0.97, 0.93, 0.95 and 0.97 (See Table II). Total weight average in system accuracy was 97.51%.

Fig. 8. Number of neurons in hidden layer versus average MSE for cross validation

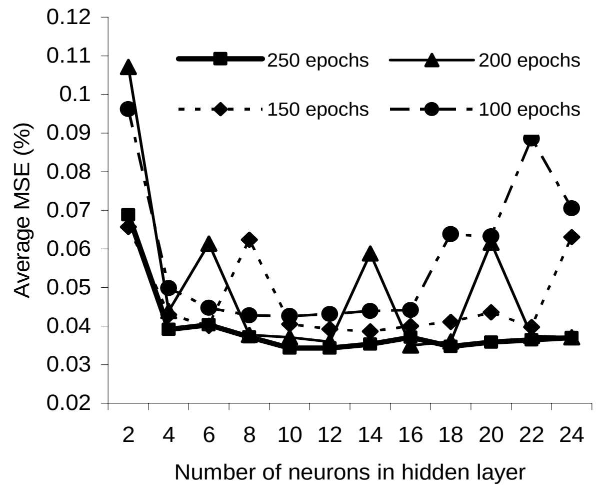
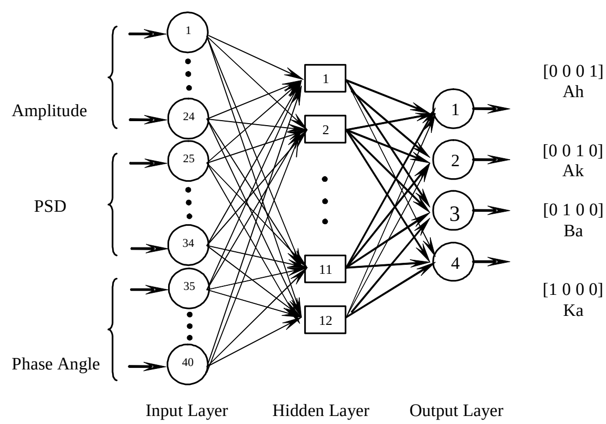


Fig. 9. The topology of a MLP neural network used in pistachio nuts separation system



CONCLUSION

In this paper a separation system, based on combination of acoustic detection and artificial neural networks, was designed for classifying four Iranian's export pistachio nut varieties. This method has high accuracy and can be adapted to recognize other pistachio varieties or in other applications such as separation of open and closed shell pistachios.

Fig. 10. Learning curve with GDM algorithm for 800 epochs

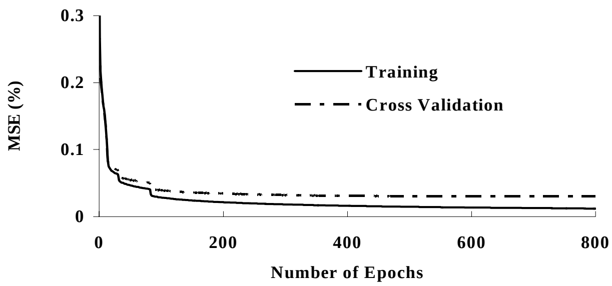


Table I. Number of correct classified nuts with 40-12-4 MLP network structure

Output / Desired	Ka	Ba	Ak	Ah
Kalehgouchi (Ka)	128	1	0	1
Badami (Ba)	1	106	3	0
Akbari (Ak)	0	3	124	0
Ahmadaghaee (Ah)	3	0	0	110

Table II. Performance of 40-12-4 MLP network structure

Performance	Ka	Ba	Ak	Ah
MSE	0.0141	0.0193	0.0270	0.0123
r	0.97	0.95	0.93	0.97
Percent Correct	96.97	96.36	97.64	99.10

MLP network was employed for pistachio nut classification. Features of pistachio nut varieties were extracted from analysis of sound signals in both time and frequency domains by means of Fast Fourier Transform (FFT), power spectral density (PSD) and principal component analysis (PCA) methods. For finding the best combination for minimum number of principle components with highest accuracy and for creating the network input vector, 37 different combinations of PCA components were fed to network as input vector. Altogether 40 features were selected for classifications: 24 amplitude features, 10 PSD features and 6 phase features. A combination of these 40 features resulted in a minimum feature number with highest classification accuracy in network training time. Selected optimal neural network for classification exhibited a 40 – 12 - 4 structure, with 12 neurons in its hidden layer. Total weight average in system accuracy was 97.51%. That means only 2.49% of pistachio nuts were misclassified. Correct separation rate of proposed optimal structure for four pistachio varieties, Ka, Ak, Ba and Ah were 96.97%, 97.64%, 96.36% and 99.10%, respectively.

The presented model works on the basis of impact sound differences, therefore is not restricted to a particular applications and therefore can be used in other applications. This technique has recently been proposed by the authors (Mahmoudi *et al*., 2005) in order to separate open and closed shell pistachio nuts.

REFERENCES

Alikhani, M., 2002. Iran Exported Worth of Non-Oil Commodities, *J. Chamber of Commerce-Iran*, 30

Cetin, A.E., T.C. Pearson and A.H. Tewfik, 2004. Classification of closed and open shell pistachio nuts using voice recognition technology. *Trans. ASAE*, 47: 659–64

Garsia-Ramos, F.J., J. Ortiz-Canavate, M. Ruiz-Altisent, J. Diez, L. Flores, I. Homer and J.M. Chavez, 2003. Development and implementation of an on–line impact sensor for firmness sensing of fruits. *J. Food Engg*., 58: 53–7

Ghazanfari, A. and J. Irudayaraj, 1996a. Classification of pistachio nuts using a string matching technique. *Trans. ASAE*, 39: 1197–202

Ghazanfari, A., J. Irudayaraj and A. Kusalik, 1996b. Grading pistachio nuts using a neural networks approach. *Trans. ASAE*, 39: 2319–24

Haykin, S., 1999. *Neural Networks*: A Comprehensive Foundation. Prentice Hall, New Jersey

Kavdir, I. and D.E. Guyer, 2002. Apple sorting using Artificial Neural Network and Spectral imaging. *Trans. ASAE*, 45: 1995–2005

Mahmoudi, A., M. Omid, A. Aghagholzadeh and A.M. Borghei, 2005. *Development of a Pistachio Sorting System Based on Acoustic Technique*. P: 164. IV Int. Symp. Pistachios and Almonds, ISHS, Tehran: Iran, 22–5 May 2005

Ministry of Agricultural Jahad-Iran, 2002. "*Global Agricultural Data Bank*", Vol. 3, No. 80/07

Pearson, T.C., 2001, Detection of pistachio nuts with closed shells using impact acoustics. *Appl. Engg. Agric*., 17: 249–53

Rumelhurt, D.E., G.E. Hinton and R.J. Williams, 1986. Learning internal representations by back-propagation errors. *Nature*, 322: 533–6

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